Improving the New Business Opportunity Process Using a Decision Support Tool and Optimization

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J.B. Hunt & Dedicated Contract Services

J.B. Hunt Transport Inc. is a Fortune 500 company in the transportation logistics industry offering services to a diverse set of customers. The Dedicated Contract Services (DCS) division of J.B. Hunt was created to provide outsourcing solutions for customers, customizing fleet operations to the customer's needs.

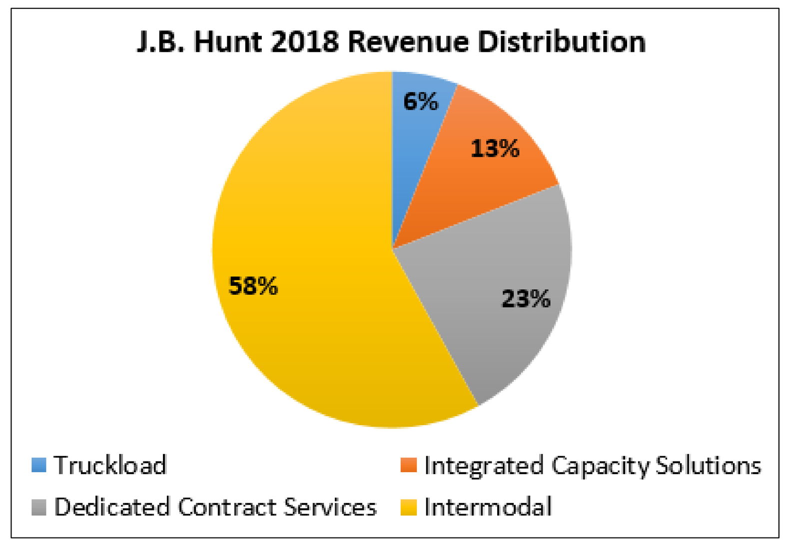


Figure 1: J.B. Hunt 2018 Revenue Distribution per Division [J.B. Hunt]

The main benefits a customer receives with DCS are:

- Brand enhancement
- Improved technology
- Efficiency
- Flexibility
- Customer service
- Customized services based on a variety of factors

Current Process & Baseline Analysis

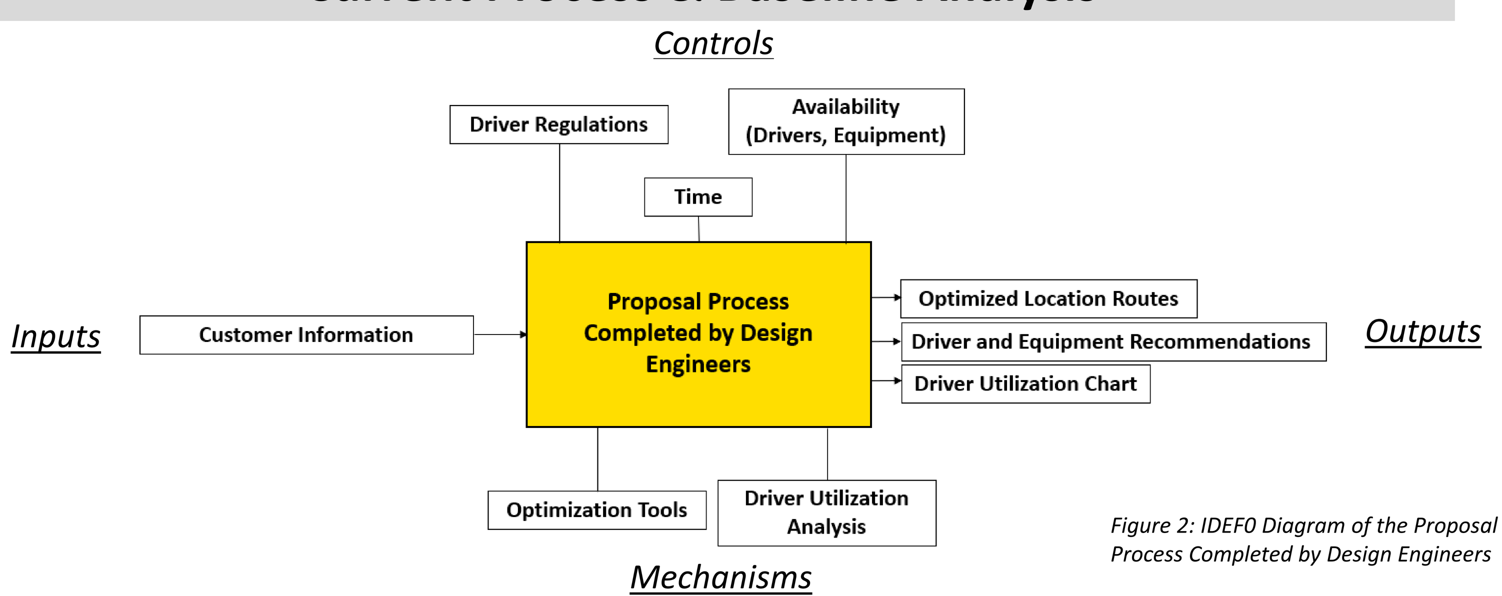


Figure 2: IDEF0 Diagram of the Proposal Process Completed by Design Engineers

- The current new customer proposal process is completed by the Design Engineer
- Inputs (from customer): routes, frequency of loads, historical shipping volumes
- Outputs: optimized location routes, driver and equipment recommendations, driver utilization charts

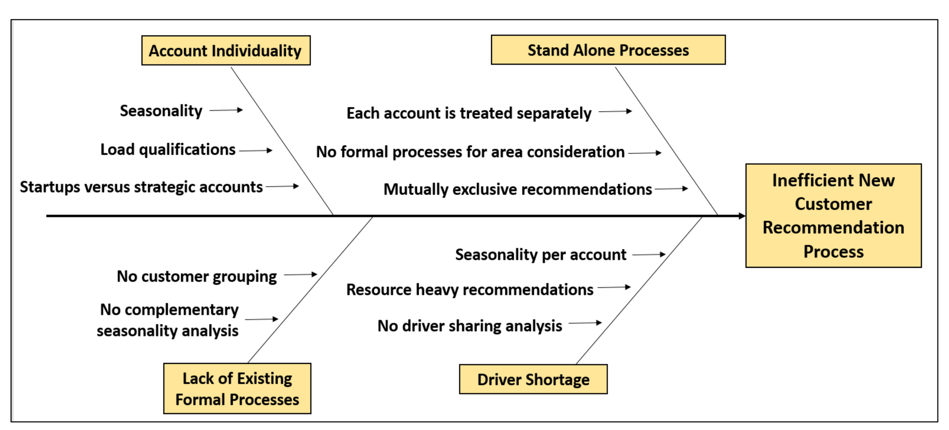


Figure 3: Fishbone Diagram of Inefficient New Customer Recommendation Process

This **fishbone diagram** allowed us to determine the sources of inefficiency in the new customer recommendation process. Specifically, our project objective will be focused on the lack of existing formal processes. Other factors impacting this process are account individuality, driver shortage, and stand alone process dictated by the specific design engineer creating the proposal.

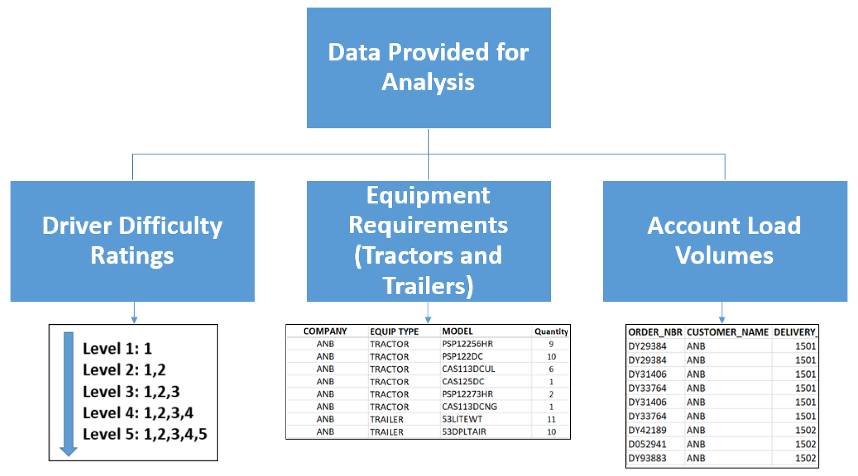


Figure 4: Data Provided and Categorized for Analysis

- **Driver Difficulty Ratings:** a measure of the skill required by a driver to perform a specific account. This is a rating 1-5, with 5 being the highest level of skill required by a driver.
- **Equipment Requirements:** all tractors and trailers used by an account to complete all jobs for a specific customer
- **Account Load Volumes:** historical data for an account by week, from week 1 of 2015 to week 34 of 2018

Problem Statement

When developing a proposal for a new customer, Design Engineers create a recommendation for equipment and drivers. Historically, this process relied on the Design Engineer's intuition and each account was treated separately which resulted in resource-heavy recommendations. J.B. Hunt wanted to find a way to increase analysis between accounts to determine areas where complementary account sharing could be implemented.

Components For Analysis:

- Equipment requirements (tractors and trailers)
- Seasonality
- Driver difficulty level
- Region (Dallas-Fort Worth area)

Complementary Accounts:
Accounts that share similar equipment (tractors and trailers) and driver workload, but have differing seasonality

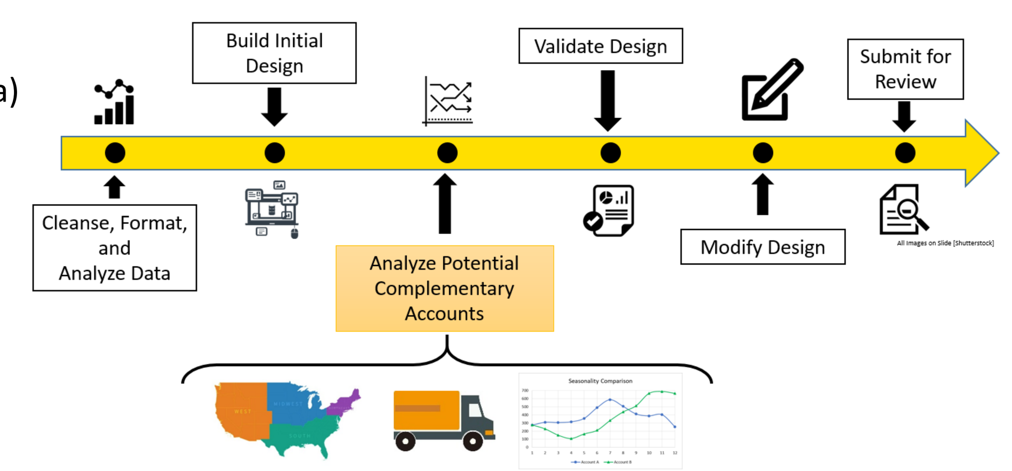


Figure 5: Proposed Process for New Customer Recommendation Process

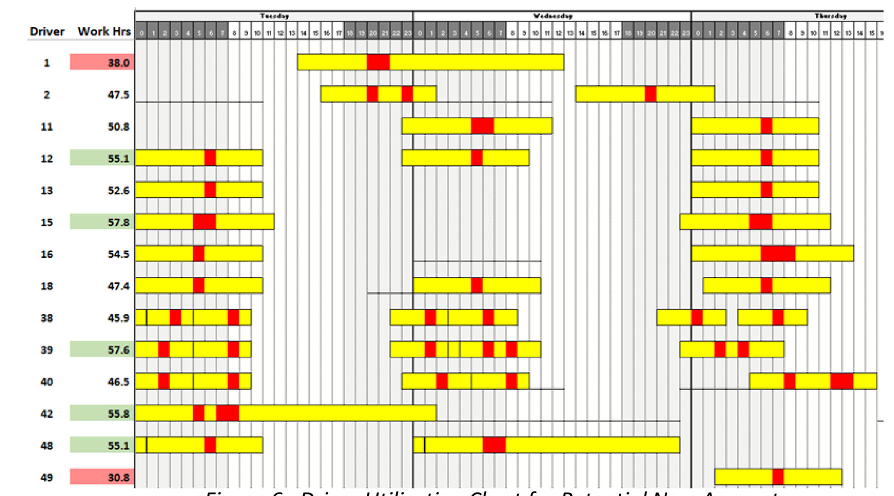


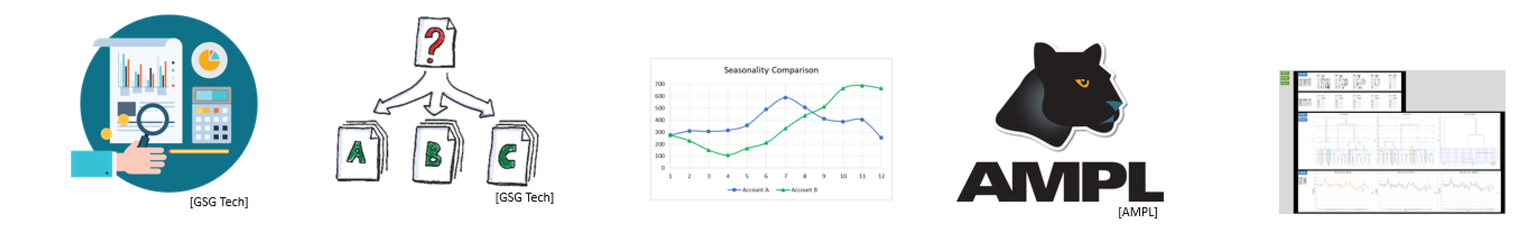
Figure 6: Driver Utilization Chart for Potential New Account

Key Performance Indicator: driver utilization and driver retention. Using complementary accounts we hope to increase driver utilization by sharing drivers between accounts.

Driver Utilization Chart: created for a new customer to demonstrate the potential schedule for drivers to meet load requirements

Solution Design

Our project was split into 5 main steps to accomplish the project objective and standardize the process of using complementary accounts to make more efficient new customer recommendations.



Cleanse and prepare data	Categorize existing account types	Examine seasonality to identify complementary accounts	Create optimization model to cluster accounts	Integrate analyses into a decision support tool
• Excel analysis • Data formatting	• Comparison testing code • Agglomerative Hierarchical Clustering (AHC)	• Forecasting in R • Correlation analysis	• Linear model in AMPL • Factors of consideration: equipment requirements, seasonality, driver difficulty score	• Excel Visual Basic tool • Factors of consideration: equipment requirements, seasonality, driver difficulty, AHC

Deliverables to Analyze Potential Complementary Accounts:

- Decision support tool – to provide design engineer with analysis methods for a new account based on components for analysis
- Optimization Model – creates a clustering heuristic for the existing accounts and produces clusters based on components for analysis

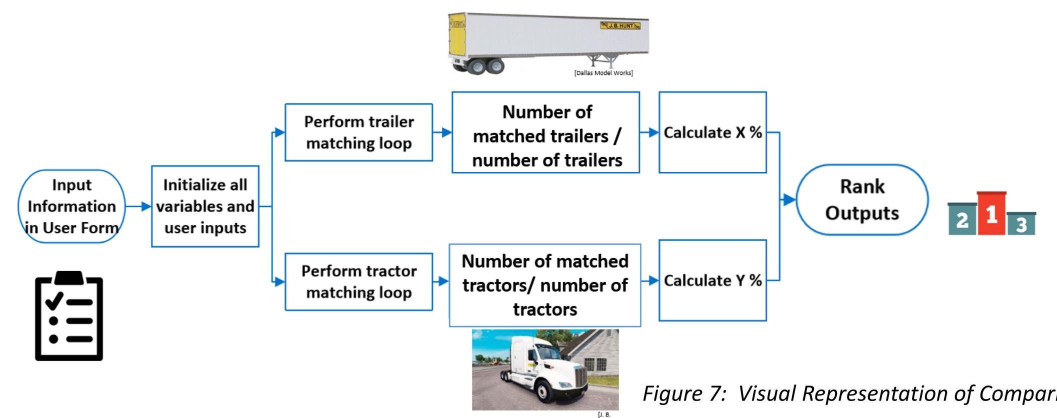


Figure 7: Visual Representation of Comparison Testing Code

Comparison Testing Code:

- Identifies the similarities in types of tractors and trailers used between a new account and existing accounts
- Runs a series of loops to calculate the percentage match between 2 accounts
- Performs analysis on tractors and trailers separately

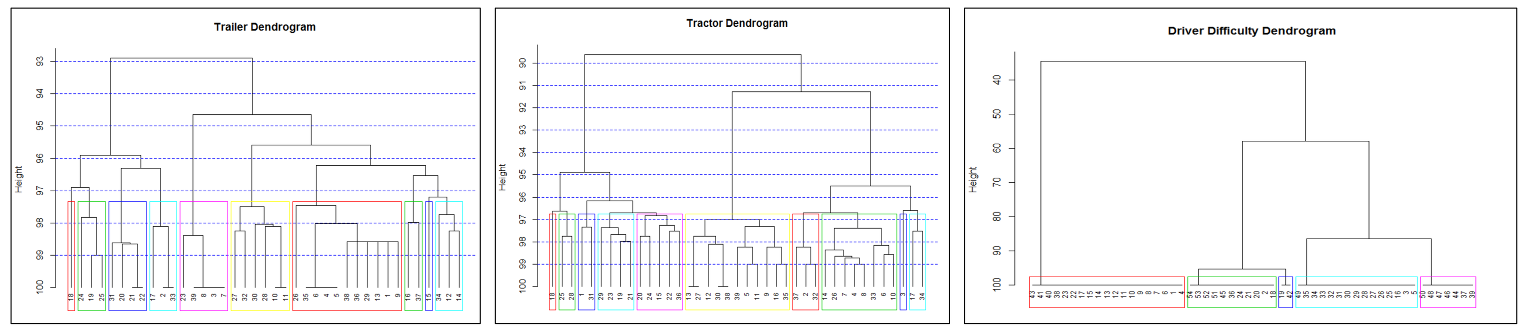


Figure 8: Dendrogram Output for AHC of Tractors, Trailers, and Driver Difficulty

Agglomerative Hierarchical Clustering (AHC) is a bottom-up algorithm that sets each data point as a single cluster, and then combines clusters at each step. We used AHC to cluster accounts based on trailers, tractors, and driver difficulty levels. This analysis was done in R.

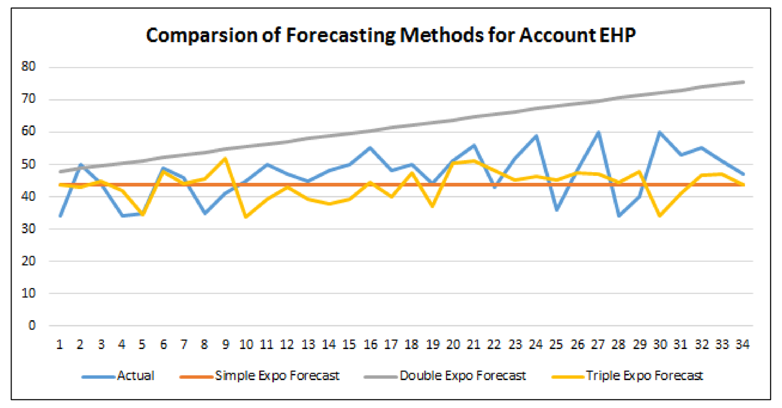


Figure 9: Graphical Comparison of Forecasting Methods for Account EHP

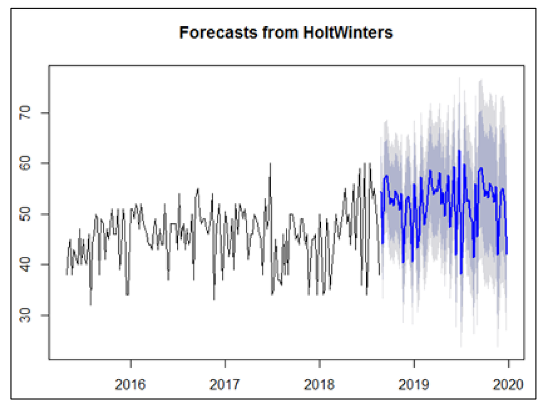


Figure 10: R Forecasting Prediction for Account EHP

Seasonality Analysis:
Triple exponential smoothing (Holt Winters method) was used to forecast account volume for each account in the data set. The forecasts are compared to identify differing peaks in seasonality.

We tested single, double, and triple exponential smoothing by forecasting the first 34 weeks of 2018 compared to the actual values for these weeks to calculate forecast error. Holt Winters was selected because it considers value, trend, and seasonality factors in the data. The Holt Winters method in R was used to forecast 52 weeks (2019 data).

Decision Support Tool:

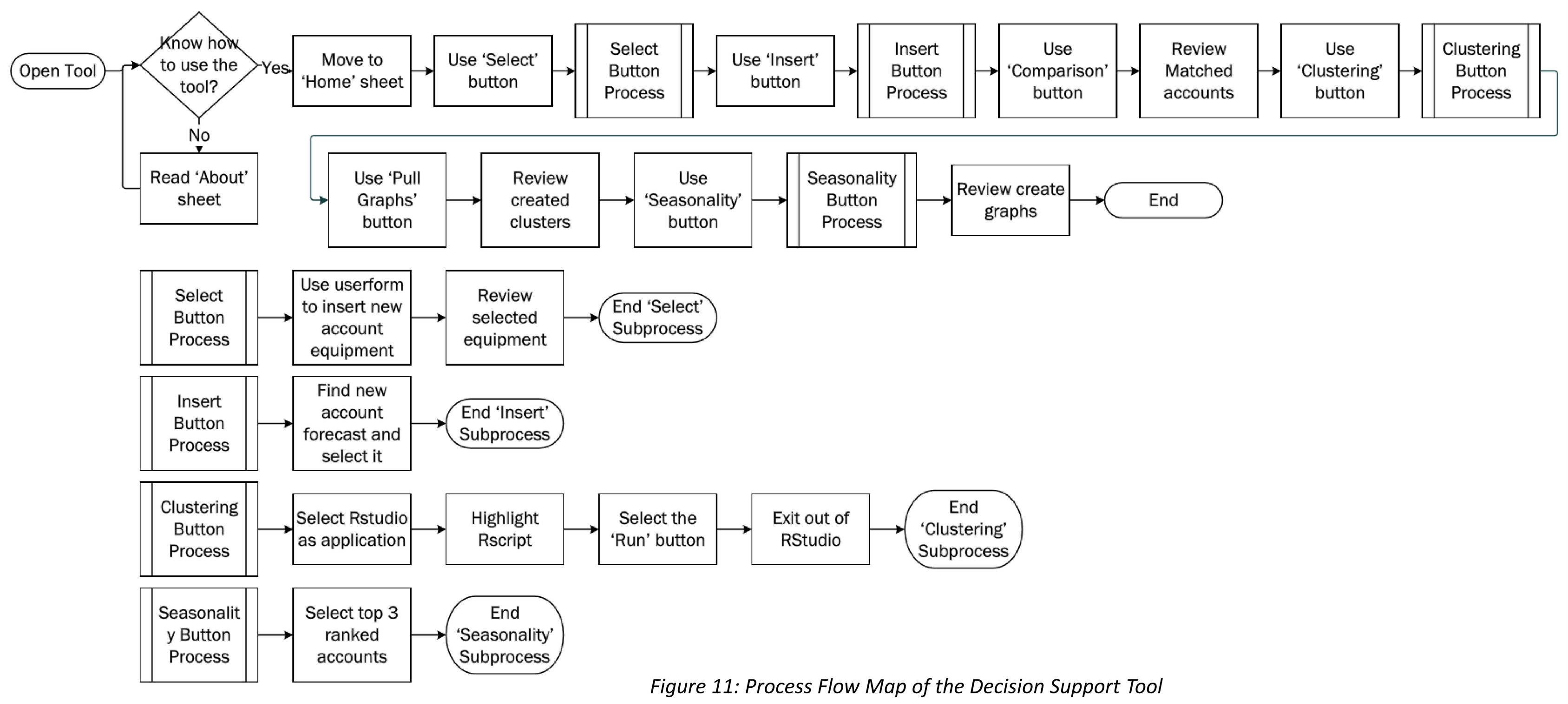


Figure 11: Process Flow Map of the Decision Support Tool

Optimization Model: a weighted objective function was used to evaluate each of the four characteristics and provide relative weight based on the most important aspects to matching complementary accounts

$$\textit{Maximize} \quad A(\textit{driver score}) + B(\textit{seasonality correlation}) + C(\textit{trailer comparison}) + D(\textit{tractor comparison})$$

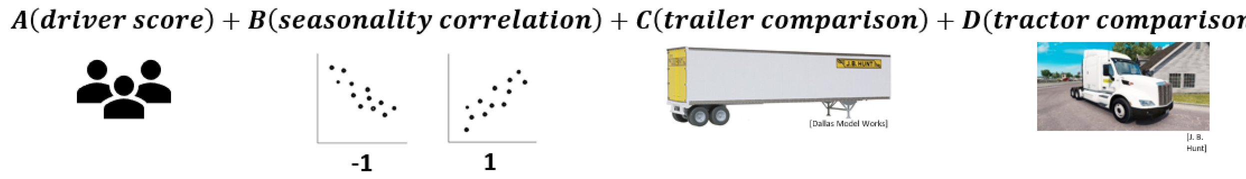


Figure 12: Optimization Model Objective Function Represented Visually

Impact & Implementation

Description	Monetary Value
Cost to hire a surge driver	$7500
Surge driver costs for top 10 DCS customers	$356.8 M /year
Project Impact (1/5 of overall surge costs)	$535,000 /year

Monetary Impact: during surge times, J.B. Hunt is required to hire drivers, usually around 20% more, to accommodate for peaks in account volume.
Design Impact: inclusion/exclusion of drivers within a design based on compliments within their network (Design Engineer)
Regional Impact: management can proactively address trends and find places to utilize excess drivers to increase driver utilization (Regional Managers)
Competitive Advantage: sales team can demonstrate added advantage to the customer over the competition based on less required drivers

Utilizing a Linear Optimization Model to Cluster J.B. Hunt DCS Accounts

J.B. HUNT

UNIVERSITY OF ARKANSAS

Background:

After creating our decision support tool, we realized there was room for improvement to help the design engineer by providing one recommendation that took multiple factors into account. We decided to create a linear optimization model for our project in order to integrate the driver difficulty level, seasonality correlation factors, and the equipment requirements. The objective function is used as a clustering heuristic to place every account in the data set into a cluster with at least one other account based on similarities.

This model utilizes a weighted objective function to accommodate for these factors and assign relative importance to each of the four items for consideration. This model was run in AMPL using CPLEX solver. We created pairwise variables to enable the use of matrices to compare accounts for simplicity, and to keep our model linear.

SEASONALITY

EQUIPMENT REQUIREMENTS

DRIVER DIFFICULTY

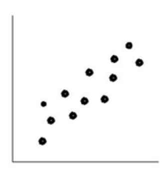
OPTIMIZATION MODEL

Objective Function:

$$\textit{Maximize}\ (A * \sum_i \sum_j driver[i,j] * X[i,j]) + (B * \sum_i \sum_j season[i,j] * X[i,j]) + (C * \sum_i \sum_j trailer[i,j] * X[i,j]) + (D * \sum_i \sum_j tractor[i,j] * X[i,j])$$

Level 1: 1
Level 2: 1,2
Level 3: 1,2,3
Level 4: 1,2,3,4
Level 5: 1,2,3,4,5

-1



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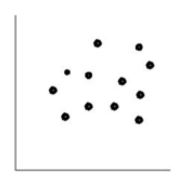


0

Potential New Account	Existing Account	
PSP12256HR	PSP12256HR	✓
53DPLT	53DPLT	✓
PSP122DC	PSP122DC	✓
CAS11660AT	53LITEWT	

75% Similar

This objective function takes into consideration the driver difficulty level, seasonality correlations, and equipment (trailers and tractors) requirements for all the accounts within the data set. This function utilizes weighted factors to give relative importance to certain aspects and seeks to maximize the fit of every account within its respective cluster for each of the 10 clusters. The optimization model is pairwise and compares all accounts i to all accounts j.

Variables:

X[i,j] $\begin{cases} 1 & \text{If account i and j are paired together in a cluster} \\ 0 & \text{Otherwise} \end{cases}$

Y[i,k] $\begin{cases} 1 & \text{If account i is in cluster k} \\ 0 & \text{Otherwise} \end{cases}$

Z[i,j,k] $\begin{cases} 1 & \text{If account i and j are paired together in cluster k} \\ 0 & \text{Otherwise} \end{cases}$

	Accounts I			
Accounts J	ANB	ARM2	CB3	CU2
ANB	1	0.843	0.981	0.365
ARM2	0.843	1	0.452	0.423
CB3	0.981	0.452	1	0.856
CU2	0.365	0.423	0.856	1

Clusters K
1: ANB, CB3
2
3
4
5

Constraints:

$$\sum_k Y[i,k] = 1 \qquad \forall\, I \tag{1}$$

Constrains the model so every account i can only be in one cluster k

$$\sum_i Y[i,k] \le 10 \qquad \forall\, k \tag{2}$$

Limits the size of the clusters to no more than 10 accounts

$$\sum_i Y[i,k] \ge 2 \qquad \forall k \tag{3}$$

Limits the size of the clusters to no less than 2 accounts to ensure each account is paired with at least one other account

$$Z[i,j,k] \le Y[i,k] \qquad \forall\, i,j,k \tag{4}$$

$$Z[j,i,k] \le Y[i,k] \qquad \forall\, i,j,k \tag{5}$$

Links together variable Z and Y. If account i is in cluster k, the value of Y would be 1, and the value of Z could be 1 or 0. The less than or equal to sign is used because accounts i and j might not both be in cluster k which would make Z equal to 0. We had to use 2 constraints to ensure every possible combination of i and j was constrained.

$$X[i,j] \le \sum_k Z[i,j,k] \qquad \forall\, i,j \text{ where } i \ne j \tag{6}$$

$$X[i,j] \le \sum_k Z[j,i,k] \qquad \forall\, i,j \text{ where } i \ne j \tag{7}$$

Compares the X and Z variables which impacts the objective function. If accounts i and j appear together in cluster k, the z variable will be equal to 1 which forces X to be 1 or 0. The X variable when equal to 1 allows for the objective function to find the maximized value of every pair. Every situation where i is equal to j is excluded from this constraint.

$$\sum_k Z[i,j,k] \le 1 \ \ \forall\, i,j \text{ where } i \ne j \tag{8}$$

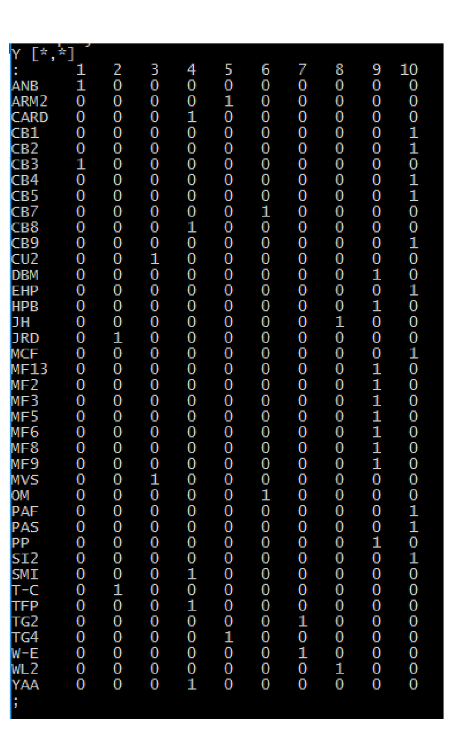
$$\sum_k Z[j,i,k] \le 1 \ \ \forall\, i,j \text{ where } i \ne j \tag{9}$$

These constraints ensure for every pair of account i and j, they can be assigned to at most one cluster together. These constraints apply to every pairing except for where account i is equal to account j.

Results:

Our linear optimization model created a clustering heuristic dividing the 39 training accounts into 10 clusters. The AMPL output of the Y variable shows each of the 10 clusters and the corresponding accounts.

This model and output allowed us to create our own clustering heuristic algorithm maximizing similarities based on driver difficulty, seasonality, tractors, and trailers. The model run time was 6 hours which presented a solution with 32% gap.



Clusters									
1	2	3	4	5	6	7	8	9	10
ANB	JRD	CU2	CARD	ARM2	CB7	TG2	JH	DBM	CB1
CB3	T-C	MVS	CB8	TG4	OM	W-E	WL2	HPB	CB2
			SMI					MF13	CB4
			TFP					MF2	CB5
			YAA					MF3	CB9
								MF5	EHP
								MF6	MCF
								MF8	PAF
								MF9	PAS
								PP	SI2

In conclusion, this optimization model was able to use four different account characteristics to create one clustering heuristic. The model successfully placed the accounts inside 10 clusters based on best fit.

One area to improve this model would be extensive sensitivity analysis on the weights associated with each part of the objective function, and on the number of clusters. This would require expert knowledge to determine what clusters best represent the system.